A hybrid Passive & Active Approach to Tracking movement within Indoor Environments,

Curran, K. (2018). A hybrid Passive & Active Approach to Tracking movement within Indoor Environments, *IET Communications*, *12*(10), 1188. https://doi.org/10.1049/iet-com.2017.1099

Published in:
IET Communications

Publication Status:
Published (in print/issue): 07/06/2018

DOI:
10.1049/iet-com.2017.1099

Document Version
Author Accepted version

IET Communications

Research Article

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ISSN 1751-8628
Received on 11th October 2017
Revised 22nd February 2018
Accepted on 6th March 2018
doi: 10.1049/iet-com.2017.1099
www.ietdl.org

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Abstract: Location-aware services enable location intelligence which provides many benefits such as personalisation of communications, consumer analytics, locating a fireman in a burning building or classifying daily activities in the home among numerous other services. Active localisation technology is where a person carries a device such as a phone or beacon which communicates with a nearby wireless access point, whereas passive localisation is where a person does not carry any electronic device but their presence in a room causes a nearby monitoring device to detect them. This is the holy grail of tracking people as they do not need to carry tracking devices. A hybrid tracking approach is where both active and passive tracking techniques can be used to complement each other in tracking individuals indoors. This study provides an overview of an indoor location framework which allows the plugging in of multiple active tracking solutions such as Bluetooth beacons in addition to facilitating passive localisation techniques to provide a flexible hybrid indoor tracking solution for pinpointing individuals in locations and accordingly classify their activities. The authors demonstrate the practicalities of such a technique when used to classify everyday activities of daily life within a typical home environment.

1 Introduction

Indoor location determination has become an important service in so far as it can track the movement of people indoors whether in the home or in shopping malls [1]. Current implementations of location intelligence (via location-aware services) in a mobile environment suffer from several issues and the choice of which technology to make use of is critical. Location tracking techniques can be divided into two main categories – active localisation and passive localisation. The distinguishing factor is the participation of the tracked individual. In a passive system, the user is not required to participate, i.e. the system can track them without any need for an electronic device to be carried or attached which sends out signals to help deduce their location. In an active system, an electronic device is carried. A significant drawback of many indoor locating technologies is the requirement to deploy a costly and complex infrastructure composed of dedicated hardware. The existing IEEE 802.11 networks and support for wireless protocols by most mobile devices make Wi-Fi a logical choice for low-cost indoor location detection. Wireless networks are capable of tracking movement through the network using a technique known as radio mapping or more commonly fingerprinting, which most IEEE 802.11 based location detection approaches are based on. Fingerprinting requires a complex setup or training phase to construct a map of pre-recorded received signal strengths (RSS) from nearby access points (APs) at every position of an interesting area [2]. The results are stored in a fingerprint database which can be queried with any RSS to identify and map corresponding locations. This fingerprint database or radio map can be used to create a model. Fingerprinting provides good accuracy but is highly vulnerable to environmental changes such as rearranging furniture or moving the APs. One method of reducing this factor is collaborative feedback allowing a continually evolving radio map, however the variation in RSS generated by different Wi-Fi chips could be a significant limitation in using a Wi-Fi-based approach [3]. An important consideration is that the decisions made when installing a wireless AP were generally to catch large congregations of users and primarily to provide the highest available throughput to those users. Indoor environments are also especially noisy with other radio devices like wireless headsets and microwave ovens causing unpredictable interference. These factors result in a coverage area which is less than ideal for fingerprinting. Fingerprinting can be divided into deterministic and probabilistic approaches. There are many models within each category each with their own pros and cons, overall the probabilistic models are the most promising with the most notable being the Bayesian-hidden Markov model.

There are several techniques available to identify and track a person's location [4]. Cross-polarised antenna systems are an attractive way to reduce equipment size while maintaining low inter-antenna correlation [5]. Akl *et al.* [6] presents a channel model based on measurements conducted in commonly found scenarios in buildings. Bluetooth low energy (BLE) beacons are fast becoming an attractive choice for an indoor location determination system since BLE beacons provide excellent accuracy and precision. Either Wi-Fi or beacons are the most appropriate choices for an accurate and reliable indoor tracking system. GPS is unsuitable indoors and radio-frequency identification (RFID) is too costly, complex and does not provide the equivalent accuracy of Wi-Fi or BLE beacons [5, 6]. Wi-Fi has good precision with low cost but is usually complex to implement [7, 8]. BLE beacons on the other hand are much easier to implement, provide excellent accuracy and precision and are very cost effective, given the prevalence of Bluetooth devices (Table 1).

This paper outlines an extensible indoor location tracking system which uses Bluetooth beacons to locate individuals indoors. The framework has been designed to work with other tracking technologies such as Wi-Fi as well. It also employs device-free passive localisation (DFpL) to classify activities whenever the person being tracked is not moving around with their mobile device. This provides a 'best of both worlds' scenario in that we can track individuals within the home when they are not using a device. The granularity of DFpL which is the term for this however can often not be as accurate as traditional active tracking (when carrying device or wearing a tag) but it can be shown to be an extremely attractive proposition especially when an environment has pre-deployed sensors as there is no additional hardware requirements. This paper expands the DFpL research by demonstrating the practicality of this approach. The system is deployed on a mobile phone (Android) and there is a web service for administrators which allows the addition of rooms, beacons and activities. The core concepts used to locate a person using passive techniques are explained in the next section which is then followed

Table 1 Summary of location determination technologies

	GPS	Wi-Fi	RFID	BLE beacons
accuracy	medium (outdoor) very low (indoor)	high	medium	high
precision	high (outdoor) very low (indoor)	moderate	moderate	high
complexity	low	high	high	low
native mobile device support	yes	yes	no	yes
dedicated hardware	yes	no	yes	yes
cost	low	low	high	low

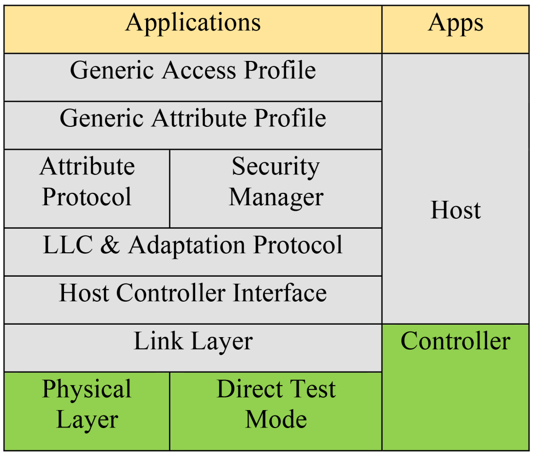


Fig. 1 *BLE protocol stack*

by a review of our location detection locator framework which may be used to implement an indoor tracking solution for determining locations and activities [9].

2 DfPL tracking

DfPL is the holy grail of indoor movement detection. DfPL allows humans to be tracked even when they possess no electronic devices which may be tracked using wireless technologies [10, 11]. It works because the human body causes a perceptible distortion to the wireless medium which allows movement detection to occur. This may prove difficult in noisy RF environments [12]. Location tracking techniques for active localisation require tracked personnel to participate actively, however passive localisation is based on monitoring changes of characteristics dependent on people's presence in an environment. There is a challenge with deploying DFpL systems as people will not be actually carrying a device which helps track movement but rather a nearby wireless AP must determine movement above a pre-determined threshold and correctly classify it as moving or non-moving.

DfPL in tracking humans in an indoor environment makes use of the fact that the human body contains just over 70% water and the resonance frequency of water is 2.4 GHz [13]. The frequency of quite a lot of commercial and home wireless networks is in the 2.4 GHZ frequency band, so a human will behave just like an absorber and attenuates the signal [14]. HABITS [15] was a framework engineered to overcome these problems by using machine learning techniques (Bayesian) which trawled historic movement patterns to increase higher levels of position accuracy. It worked by recording the movement of users and their path vectors over a period so as to predict the most likely paths that they would travel. This allowed filling in the blanks in real-time position tracking when users entered radio-frequency (RF) signal black. Further work concentrated on the problem of identification of multiple individuals moving simultaneously using DfPL [16]. This was achieved for two parties using smoothing algorithms to filter the RSS indicator (RSSI) recordings. Nuzzer is a large-scale DfPL localisation system, which tracks entities in real environments, rich in multipath [17]. They use probabilistic techniques for DfPL localisation of a single entity in typical office buildings localising them into coarse-grained zones. Results show that Nuzzer gives location estimates with <2 m median distance error.

Mobile phones can act as activity detectors by monitoring disturbances in the radio signals detected, thus allowing decisions to be made on whether movement is occurring near the phone. Phones are ubiquitous in modern life and possessing the ability to detect movement opens a variety of domains which can take advantage of this movement detection. Competing measures to detect movement include cameras but this can be a significant drain on battery life. Sound recognition is also a possibility, but this too is processor intensive and prone to failure when no words are spoken [18]. There is minimal overhead in movement detection with DfPL. It is also less intrusive than camera-based techniques.

Movement is determined when RSSIs above a threshold a number of times in a period [19]. Here the phone becomes the AP. Example use case scenarios include an alarm clock which ceases to sound once it determines the person is up and moving around. Another is where intruders are detected. Another potential application is in healthcare where a phone can be used to monitor patient movements and provide inputs to an alert system [20, 21]. There are threshold levels which must take care of allowing for movements of pets so as to avoid false positives. The room level resolution for accurate detection is ideally at <1 m.

3 Bluetooth low energy

BLE is a variation of classic Bluetooth [22]. It aims to provide a power-efficient technology for controlling applications where the amount of actual data sent is low. Examples would include sensor values or control commands. BLE power consumption is reduced to between 50 and 99% in comparison to standard Bluetooth power consumption. The lifetime of BLE devices powered by a coin cell battery can range between 2 days and 14 years. An enormously low power consumption is perfect for devices which need to run off a tiny battery for extended periods but the power of BLE is its ability to work with the billions of Bluetooth enabled devices currently on the market. Using Bluetooth for location determination is mainly achievable when many known location stationary devices exist and the trilateration technique is used to determine location [23].

3.1 BLE protocol

Although the classic Bluetooth and BLE protocol stacks share many common features, BLE includes some significant differences. Like Bluetooth classic, the BLE protocol stack has two main parts: the controller and the host. The link layer and physical layer are part of the controller. The logical link control and application protocol, the attribute protocol, security manager protocol, generic attribute protocol and generic access protocol (GAP) are part of the host. The controller and host communicate through a host controller interface. The GAP stipulates device roles, management of connection establishment, security and procedures of device discovery. Bluetooth GAP specifies broadcaster, observer, peripheral and central roles. Devices may support many roles but they can only play one role at any time. Application layer functionality not defined by the Bluetooth specification sits on top of the host. The BLE protocol stack is shown in Fig. 1.

It is worth noting that the theoretical maximum range distance for both Bluetooth protocols is highly 'theoretical' and more realistic/practical values would be ∼10–20 m in a furnished room with possible presence of static and moving scatterers [24, 25].

The BLE protocol stack features a smart host control which places intelligence in the controller which allows the host to sleep for longer periods. It also allows it to be woken up by the controller only when needing to wake up. This is one of the primary techniques BLE uses to achieve its low power consumption, however the differences in the controller render the BLE controller incompatible with classic Bluetooth controllers. This means that a device which implements BLE cannot communicate with classic

Table 2 Bluetooth and BLE comparison [26]

Technical specification	Classic Bluetooth technology	Bluetooth smart technology
distance/range (theoretical max.)	~10–100 m	~10–100 m
application throughput	0.7–2.1 Mbit/s	0.3 Mbit/s
active slaves	7	implementation dependent
security	56–128-bit and application layer user defined	128-bit AES counter mode CBC-MAC and app layer user defined
robustness	adaptive fast frequency hopping, FEC, fast ACK	adaptive freq hopping, lazy ack, 24-bit CRC, 32-bit integrity check
latency (from a non-connected state)	typically 100 ms	6 ms
minimum time to send data	100 ms	3 ms
voice capable	yes	no
network topology	scatternet	scatternet
power consumption	1 W as the reference	0.01–0.50 W
peak current consumption	<30 mA	<15 mA
service discovery	yes	yes
profile concept	yes	yes

Bluetooth device. Many devices implement both protocol stacks and are known as dual-mode devices.

Another technique used by BLE to reduce power consumption is the number of frequency channels used for device discovery. Known as advertising channels classic Bluetooth uses 32 channels which are scanned to determine whether any others are seeking to make a connection. BLE uses three channels for this task. This reduction significantly reduces the amount of time required to scan for devices, classic Bluetooth takes 22.5 ms to scan while BLE takes 0.6–1.2 ms. However, this reduction comes at a cost as there is a higher chance that another device is broadcasting on the same signal, interfering with the BLE signal. An overview of the technical differences between classic Bluetooth and BLE is shown in Table 2.

Any BLE compatible device, such as a smartphone, can take on the role of a beacon. The term beacon however generally refers to a single purpose dedicated hardware. They are mostly designed to be low cost and have a long lifetime that transmits data in the form of Bluetooth beacon frames. Beacons are broadcast-only. They are also non-connectable devices but they can become connectable. They achieve this by switching the GAP from broadcaster role to a peripheral role which allows the beacon to be updated over the air.

The hardware inside a beacon consists of a microcontroller with a BLE radio chip and a battery. The radio chip is commonly manufactured by two major companies: Texas Instruments and Nordic Semiconductor. Bluegiga and Gimbal are two other suppliers of BLE chipsets, however they use underlying hardware from Texas Instruments and their own custom firmware before selling to beacon vendors. The hardware suppliers mentioned have over 95% of the BLE chipset market share. Beacons can be powered using three main approaches: DC power supply (USB, mains), batteries (AAA, lithium) and battery harvesting (solar, kinetics). If a DC powered approach is used, then power consumption is likely a less important consideration, however this restricts beacon mobility as power outlets may not be available without running new wiring. Energy harvesting is becoming more common as components get cheaper but the inexpensive and mobile battery approach is most common. Kontakt beacons use a Nordic chipset and a 3 V lithium ion coin cell batteries which provides up to 1000 mAh of stored power. Every beacon has specific firmware which enables the hardware to operate. The firmware controls several key parameters which can be configured. The two most critical parameters, which have significant effects on both quality/strength of signal and battery life, are transmission power (TX power) and advertising interval. In RF theory, one factor that determine the range which radio waves can be detected is the output power of the radio transmitter. This transmission power or TX power is usually chosen depending on circumstances such as proximity of nearby Bluetooth devices (coexistence), a desire to reach a greater area (range) or environmental considerations such as obstacles blocking line of sight. A higher TX power is proportional to a reduction in battery lifetime therefore trade-off considerations need to be made. Advertising interval is the rate or frequency that a beacon emits a signal. An interval of 100 ms means the signal is emitted every 100 ms. A higher advertising interval allows more time in sleep mode but increases detection latency which is the delay between the receiving device being within the beacons range and the successful parsing of the beacon broadcast by the receiving device. A higher advertising interval also increases beacon battery life.

3.2 Broadcasted data formats

At the top of the BLE protocol stack, there are several industry standard protocols which detail beacon payload formats. These specify beacon frames types, which enables standardisation of how beacons communicate with a device acting as a receiver. Several protocols exist which may be propriety or open source. There are two primary vendor defined protocols – iBeacon and Eddystone.

3.2.1 iBeacon: The iBeacon protocol is a proprietary protocol meaning that the iBeacon protocol cannot be unofficially extended and complete control of the protocol format lies with Apple. The iBeacon frame type is composed of five parts. The iBeacon prefix, a Universally Unique Identifier (UUID), a major, a minor and TX power. The iBeacon prefix is used to indicate that the beacon uses the iBeacon frame format. TX power determines proximity from the beacon. TX power is the strength of the signal 1 m away and is calibrated and hardcoded in advance.

Devices can use the TX power as a baseline to receive distance estimates. The remaining three parts are used to group and identity beacons. The UUID differentiates a group of related beacons and is usually used by one application or organisation. The major distinguishes a smaller set of beacons within the larger set and the minor identifies a specific beacon within that subset.

3.2.2 Eddystone: The Eddystone protocol was released by Google in July 2015. Eddystone defines three frame-type formats which are transmitted by the beacon device: Eddystone-UID, Eddystone-URL and Eddystone-TLM. Eddystone-TLM transmits telemetry information about the beacon including battery voltage and device temperature. The Eddystone-UID frame broadcasts a 16-byte beacon id composed of a 10-byte namespace and a 6-byte instance. The namespace is used to group a set of beacons. The instance id identifies devices in a group. This division may also be used to optimise BLE scanning such as filtering only on the namespace. The complete beacon id may be useful in mapping a device to a record in a database – which may, for example, be a pre-defined location. The Eddystone-URL frame broadcasts a uniform resource locator (URL) using a compressed encoding format. The decompressed URL can be used by any client that receives it to access the internet which may be anything from an information page to an app download page. A beacon can only broadcast one frame type per broadcast event but some beacons support the ability to alternate frame types between broadcast events, e.g. transmitting an Eddystone-URL frame followed by an Eddystone-UID frame. The Eddystone packet format is shown in Fig. 2. The only piece of useful information an iBeacon can send out is the UUID, however the Eddystone protocol can send out both a UUID and a URL. This means that iBeacon requires a dedicated application or rather some kind of registry to make use of information gained from beacons. For any kind of one-time transaction or use, sending out a URL is less troublesome and allows users, who are unaware of nearby beacons, to receive notifications on their device, depending on built-in device support. Other than support for multiple frame types, there are several other

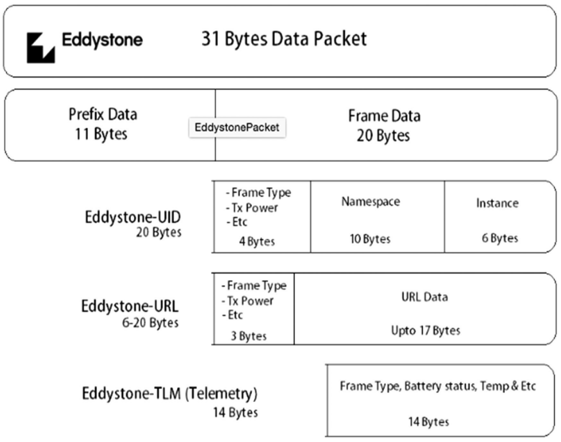


Fig. 2 *Eddystone packet format*

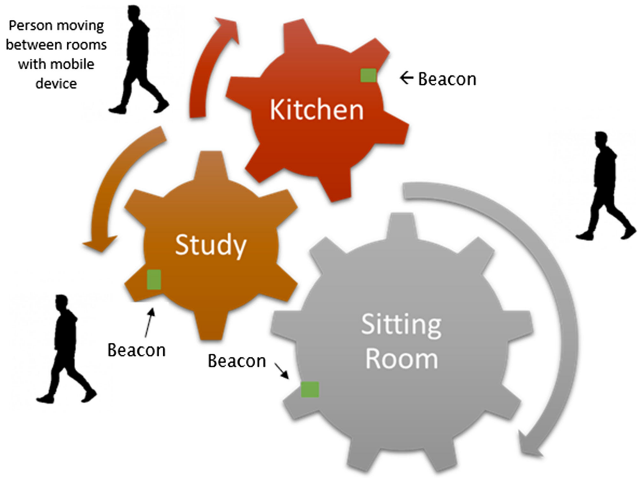


Fig. 3 *System architecture*

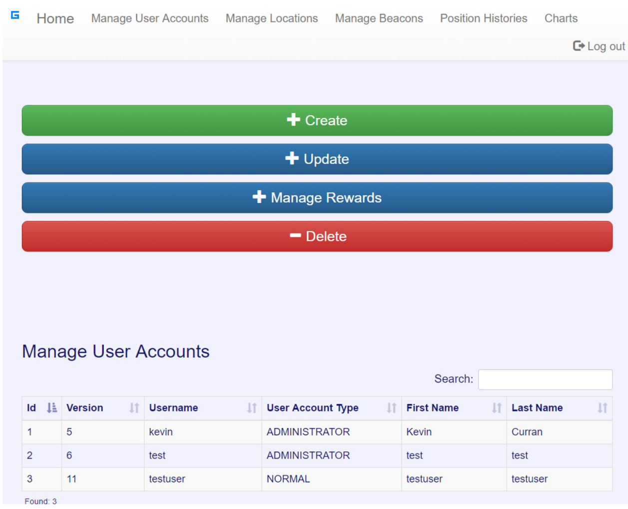


Fig. 4 *Main web application user accounts page*

key differences between the iBeacon and Eddystone frame formats. Primarily, iBeacon is supported by iOS devices only while Eddystone has official support from both iOS and android. This limits use of iBeacons because lack of support by android cuts out 82% of the worldwide smartphone market. Eddystone is an open protocol meaning the specification is available to anyone whereas iBeacon is a proprietary protocol owned by Apple. This allows developers and organisations to tailor the protocol to suit their own needs rather than using the protocol specified by Apple. Eddystone promises features to address privacy and security concerns through ephemeral identifiers (EIDs) which change. These allow only authorised clients to decode them. EIDs are not yet supported but Google has said that they will publish the technical specifications of the design soon something that Apple has not yet addressed with iBeacon.

4 Locator framework

An architecture diagram for the system is shown in Fig. 3 displaying several users who have devices which are communicating with a beacon. The mobile devices also communicate with an application/database server. This allows the location of the device to be determined. The device is the active partner. The systems database stores any long-term application data, including all information relating to locations, positions within rooms and beacon metadata such as assigned positions. The database also holds information relating to application users, activities and position histories (positions which the user has visited). Since this data is generated based on current data, no statistical data needs to be stored. All layers of the web application make use of the open source Spring framework. Spring is an application and inversion of control container for Java web applications which relies heavily on the use of interfaces and XML wiring to inject dependencies (or configurable properties) into other classes. The use of dependency injection is one of the most effective ways of reducing a class' dependency on another class and greatly aides in keeping classes loosely coupled, reusable, extensible and highly testable. The web application makes full advantage of these features and the isolated modules.

It is evident that there are many techniques available to identify and track a person's location. The problem this research overcomes is the implementation of a system capable of identifying a person's location in an indoor environment combined with determining activities using DFpL techniques. BLE beacons are an attractive choice for an indoor location determination system since BLE beacons provide excellent accuracy and precision. A beacon system is also feasible since its complexity is comparatively low; although the system will require use of dedicated BLE beacon devices, they are relatively cheap hardware given the prevalence of Bluetooth devices. Modern mobile devices come equipped with Bluetooth hardware as standard and natively support BLE connections allowing most users to immediately make use of the system. When implementing a beacon system, a decision needs to be made regarding the broadcasted packet format. Although a new standard, Eddystone usually offers the greatest flexibility and is becoming the preferred approach to implementing a beacon system. Therefore, we adopt the Eddystone frame format. This section outlines the architecture of the systems.

4.1 Architecture

The beacons deployed were Kontakt smart beacons. These supported the Eddystone frame format and can broadcast an Eddystone-UID. The beacons supported features such as simultaneous multi-frame format broadcasting. They were all fitted with new batteries to eliminate battery power bias in tests. Given the relatively short range in which beacons work, each beacon's transmission power was set at low settings. This allowed the beacons to last for long periods of time which the apps estimate at around 38 months. Beacon advertising intervals were set at 100 ms to guarantee that beacons are located by the mobile app. This helped us achieve optimal distance measurements.

The system database stores any long-term application data, including all information relating to locations, positions within locations (e.g. rooms) and beacon metadata such as assigned positions. The database holds information relating to application users, activities and position histories (positions which the user has visited) (see Fig. 4).

4.2 Passive localisation

Our system also can monitor the environment when no movement takes place with the phone. This allows us to classify activities to supplement the active location determination which occurs through the beacons. Indoors, RF signals bounce around and factors such as curtains, thick walls, people and temperature can each affect the

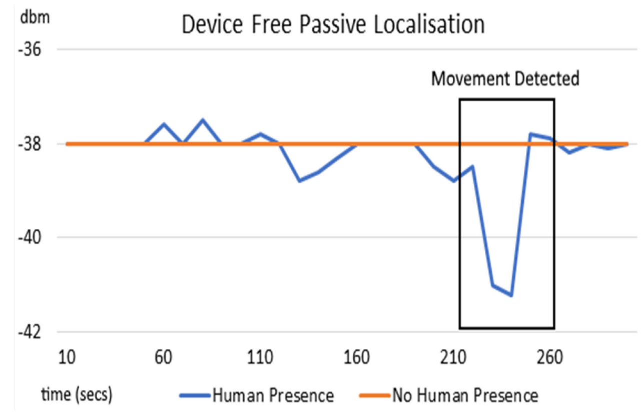


Fig. 5 *DFpL picking up human movement*

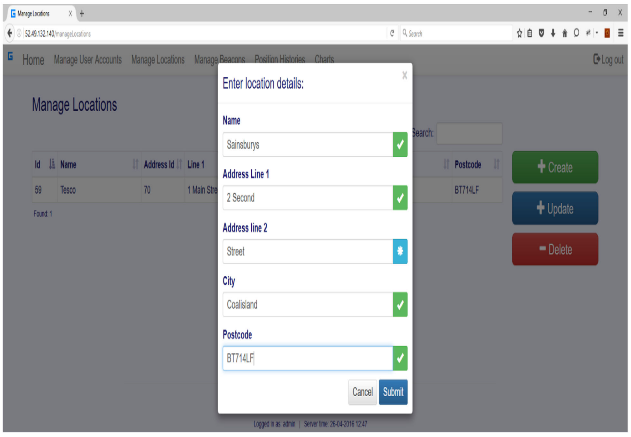
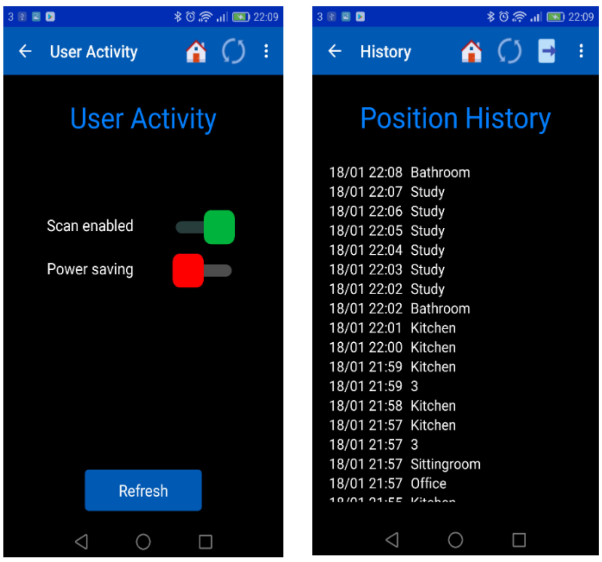


Fig. 6 *Entering new location details*



a *b*

Fig. 7 *Sample Mobile Screens*
(a) Beacon scan frequency, ***(b)*** Position histories

way a signal propagates through the air. The human body also interferes with wireless signals such as coming from a standard household AP. We extend our previous work in detecting human movement by using the mobile phone lying static whilst connected to an off-the-shelf Wi-Fi 802.11 AP [27] to ascertain movement. The human body has around 70% water which causes variances in the RSSI and this disturbance in the signal strength of the wireless communication can be significant. Monitoring changes in the RSSI, one can detect human presence or when the monitoring device is moving. The Blue line in Fig. 5 shows DfPL in action.

Table 3 Locations visited and activities

Step	Location	Position	Duration, s	Activity
1	kitchen	sink	65	standing
2	kitchen	fridge	15	standing
3	bathroom	wash basin	30	standing
4	kitchen	fridge	20	standing
5	study	sofa	90	sitting
6	study	sofa	10	standing
7	kitchen	sink	40	standing
8	bathroom	wash basin	45	sitting
9	study	sofa	100	sitting

The system collects RSSI data for each packet received and classifies which RSSI perturbations indicate the presence of a person in the sensing area. Pattern recognition networks are feedforward networks which can classify input vectors based on target classes [28]. The feedforward networks are also known as multilayer perceptron (MLP) networks. MLP networks are called universal approximators as they can approximate any non-linear input–output relationships between inputs and outputs and were used here as the core tracking algorithm.

5 Evaluation

Beacons were deployed in various locations. Each location was allocated multiple fictional positions (e.g. hall, stairs, entrance, sofa) and each was associated with a beacon. The admin user can login to the application and configure beacon data. The configuration most common was to assign beacons to specific positions. Fig. 6 illustrates this process.

Each time a user goes within 0.5 m of a beacon they are recorded at that location and position history is saved. The total time spent at each position is recorded. Table 3 shows the positions in testing.

The user's activity display is updated at each stage indicating that position histories were successfully being saved. The power level for beacon scanning is shown in Fig. 7*a* and position history is shown in Fig. 7*b* within the app. Fig. 8 shows locations on the web application.

The DFpL aspect is invoked when no movement is detected within 60 s. The phones RSSI values are probed to ascertain whether the person is moving or staying still. There are only two activity classifications in the system but this can be expanded to determine other activities such as washing, exercising or sweeping in the future. Fig. 8 shows the position histories recorded for testuser4 when moving between locations.

The DFpL technique can complement the determination of which room a user was in. We use RSSIs to give us a relative measurement of the RSS at the device and apply probabilistic smoothing and prediction techniques to overcome the noise in the signal.

The mobile phone acts as the 'access point' and becomes the device which detects movement. This supplements the active mode of determining which room the person is in and gives us more details on activities such as shown in Table 4.

The last ID points to the last beacon picked up. At times, this may be wrong if a movement is made to another position in between scans. If the movement is also unclear as to movement, then it will respond with a standing/walking classification.

5.1 Future work

The Internet of Things (IoT) has emerged as a leading factor in the future state of the Internet. Once millions of home appliances are connected to the IoT, there is a real opportunity for integrating DFpL techniques. One possibility to extend our work is delivering a human detection in disaster situations in conjunction with the IoT public infrastructure of sensors. There are still challenges in using the public IoT for emergency response teams as they have to rapidly assess disasters where people are trapped. Their main concern is to figure out who is trapped, how many and where.

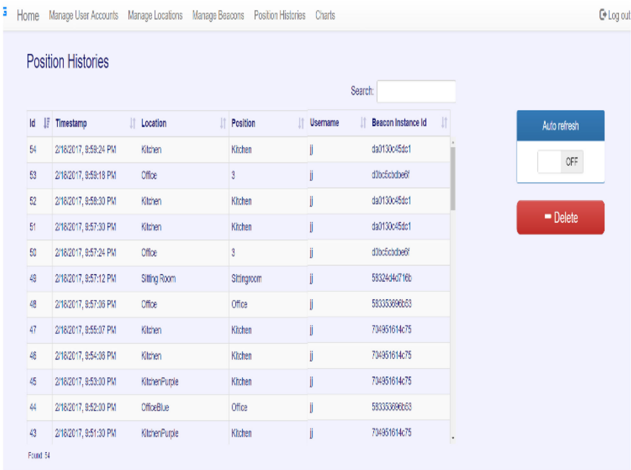


Fig. 8 *Position histories displayed in web portal for testuser4*

Table 4 Activities

Last ID	Location	Position	Duration, s	Activity
Da0130c45dc1	study	window	28	standing
D911eb22abed	kitchen	fridge	11	standing
58335369b53	bathroom	wash basin	28	standing
D911eb22abed	kitchen	fridge	5	standing
Da0130c45dc1	study	sofa	40	sitting
Da0130c45dc1	study	sofa	10	walking
Da0130c45dc1	study	window	30	standing
58335369b53	bathroom	wash basin	15	standing
Da0130c45dc1	study	sofa	82	sitting

DFpL can assist by also integrating with existing wireless sensors and artificial intelligence techniques to allow positioning to be achieved at a reasonable cost in terms of time and infrastructure and this proposal aims to build such a system. We also see potential in tracking people without on-body sensors in indoor heating scenarios. For instance, smart energy meters provide consumers with transparent data on energy consumption which has been shown to reduce consumption; however connected smart thermostats can also be used to integrate with heating systems so that decisions can be made on when to turn the heating on based on fluctuating energy costs. Tracking people indoors allows room to be heated on a 'as-used basis' thus saving money.

6 Conclusion

Determining the position of a person indoors can be important for many activities not least monitoring elderly people in their homes so that they can remain more independent. There are many location determination technologies with various advantages and disadvantages associated with each. This paper outlines a passive/active hybrid system, with a mobile device being carried inside a house and pinpointing the user in accordance with various Eddystone beacons located throughout. These record locations and our system provides both a mobile and web based component. We believe Bluetooth beacon technology is a cost-effective means of tracking people indoors. Our framework also integrates passive (DFpL) modes of tracking activities so after a set period when no more transit between beacons occurs and the mobile phone is static, the phone turns into passive mode and monitors for nearby movement to attempt to ascertain whether the person is carrying out an activity. This therefore results in hybrid framework combining both passive and active modes of indoor localisation.

7 Acknowledgments

This work was funded by the Royal Academy of Engineering under their Royal Academy of Engineering Senior Research Fellowship scheme.

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